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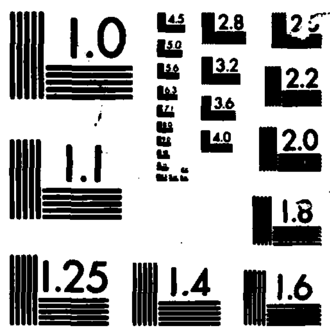

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Decision Making Under Ambiguity

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Ellsberg's paradox demonstrates that ambiguous or vague probabilities derived from choices between gambles are not coherent. A descriptive model of judgment under ambiguity is developed in which an initial estimate serves as a starting point and adjustments are made for ambiguity. The adjustments involve a mental simulation in which higher and lower probabilities are considered and differentially weighted. Implications of this model include ambiguity avoidance and seeking; sub- and superadditivity of complementary probabilities; dynamic ambiguity; and reversals in the meaning of data. Three experiments involving Ellsberg's paradox and the setting of buying and selling prices for insurance and warranties test the model. A choice rule under ambiguity is developed that implies a lack of independence between ambiguous probabilities and the sign of payoff utility. The applicability of the model to the case where probabilities are explicitly stated is considered, including the handling of context effects.

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Decision Making Under Ambiguity

The study of decision making under uncertainty has been dominated by a single approach – the closely related theories of expected utility (EU) and subjective expected utility (SEU). As formulated and axiomatized by von Neumann and Morgenstern (1944) and Savage (1954), these theories rank amongst the most important in 20th century social science. They have had a profound influence on the manner in which social scientists (in particular, economists, psychologists, statisticians, sociologists, political scientists), describe choice under uncertainty. Moreover, they have provided the foundation for prescriptive appoaches to decision making (e.g., decision analysis, see, Raiffa, 1968; Keeney & Raiffa, 1976). In one area, however, EU and SEU (hereafter called "utility theory") have met with mixed success. This is represented by a host of experiments on choice behavior, conducted principally by psychologists but also by an increasing number of economists (for a comprehensive review, see Schoemaker, 1982). On the one hand, utility theory has been enormously fruitful in providing a framework within which choice can be studied. On the other, it has failed to predict certain phenomena, resulting in so called choice paradoxes or anomalies. Furthermore, these failings have been noted for several decades (cf. Edwards, 1954, 1961).

Utility theory has nonetheless proven to be remarkably resilient to the experimental evidence that has accumulated against it. Indeed, we make this remark despite the fact that several recent alternative theories succeed in explaining several choice paradoxes (e.g., Bell, 1982; Chew & MacCrimmon, 1979; Kahneman & Tversky, 1979; Machina, 1982; Quiggin, 1982). We believe that three factors have contributed to the longevity of utility theory: (1) the criterion of maximizing expected (or subjectively expected) utility follows logically from a parsimonious set of axioms. In addition, each axiom specifies a reasonable principle (e.g., transitivity) such that it provides a description of how a "rational" actor might behave; (2) the theory has provided a useful framework for deriving empirically testable propositions in many areas of applied economics, e.g., finance, marketing, law, and so on; (3) the theory is difficult to falsify with naturally occurring data since exogenous variables can be called upon to explain violations of predictions. Moreover, tests of utility theory are not as rigorous as they seem in that specific alternatives to the theory are rarely considered

(for exceptions, see Kunreuther, 1976; Thaler, 1980). In practice, tests of the theory have not followed a "strong inference" approach (Platt, 1964).

In our view, both utility theory and its alternatives fail to capture three important elements that characterize risky decision making. (1) *The nature of uncertainty in choice*. The dominant metaphor used to conceptualize risky decision making involves choices between explicit gambles. Moreover, in both experimental and theoretical work, this notion is made operational by using explicit gambling devices such as dice, urns, bingo cages, and the like. However, we argue that the nature of the uncertainty people experience in real world decisions is often quite different from that inherent in gambling devices. (2) *Effects of context*. The gamble metaphor allows one to study the structure of decisions within a particular context (i.e.,the gambling context). However, people are highly sensitive to contextual variables and changes in context can strongly affect the evaluation of risk. (3) *Dependence between probabilities and payoffs*. All models proposed to date maintain the assumption that utilities and probabilities combine independently in determining the overall worth of risky options.We believe that payoffs can systematically affect the weight given to uncertainty, especially in the presence of ambiguity.

Purpose and Plan of Paper

Our focus in this paper concerns the first issue raised above -- the nature of uncertainty and its representation in theories of choice. The other two issues are briefly considered, particularly in light of the model developed for dealing with judgments under ambiguity. The paper is organized as follows: we first discuss the difference between exact probabilities and the more realistic ambiguous probabilities that characterize most decision making situations. In this regard, we consider the paradox due to Daniel Ellsberg (1961), in which choices under ambiguity violate Savage's (1954) SEU model. A quantitative, psychological model of how people assess uncertain probabilities is then developed and various implications are derived. Three experimental studies that test the model are presented. These deal with variations of Ellsberg's paradox, and the setting of buying and selling prices for an insurance policy and a warranty. Finally, our results and model are discussed with respect to a choice rule for decision making under ambiguity, and extensions of this rule to situations

where probabilities are precisely known.

The Nature of Uncertainty and Ambiguity

There are important psychological differences in the way people experience the uncertainty inherent in gambling devices as compared with those faced in everyday life. In gambling devices, the nature of uncertainty is explicit since there is a well defined sampling space and sampling procedure. In contrast, when assessing uncertainty in real world tasks, the precision of the gambling analogy can be misleading. Specifically, beliefs about uncertain events are typically loosely held and ill-defined. Moreover, feelings of uncertainty are not limited to random influences that affect outcomes from a well-defined process (e.g., the proportions of different colored balls in an urn), but can extend to uncertainty about the underlying data generating process itself. In short, ambiguity or "uncertainty about uncertainties" is a pervasive element of much real world decision making. We now turn to an important demonstration of this fact by discussing Ellsberg's paradox (Ellsberg, 1961).

Ellsberg used the following example to demonstrate that uncertainty in choice is not totally captured by the concept of a "probability." Imagine two urns each containing red and black balls. In Urn 1, there are 100 balls with unknown proportions of red and black. Urn 2 contains 50 red and 50 black balls. Now consider a gamble such that, if you bet on red and it is drawn from the urn, you get a $100 payoff; similarly for black. If, on the other hand, you bet on the wrong color, the payoff is $0. First, consider Urn 1 and ask yourself whether you prefer, or are indifferent to, betting on a red or black ball (designated R_1 and B_1, respectively). Most people are indifferent between red and black thereby implying that the subjective probabilities of the two events are equal; i.e., $p(R_1) = p(B_1) = .5$. Next consider the choice of balls in Urn 2, where the proportion of red and black is known to be .5. Again, most people are indifferent between R_2 and B_2, implying that $p(R_2) = p(B_2) = .5$.

Imagine that you are now asked to indicate whether you would prefer to draw a red from Urn 1 (unknown proportion of red) or from Urn 2 (proportion of red = .5). When faced with this question, many people prefer Urn 2 (rather than express indifference). Note that the choice of Urn 2 over Urn 1 implies that $p(R_2) > p(R_1)$. However, from the previous choices, $p(R_1) = .5$ and $p(R_2) = .5$. Hence, there is a contradiction between the probabilities derived from choices within the

urns, to those derived from choices between the urns. Finally, consider being asked to choose between Urns 1 and 2 if a black ball is to be drawn. Again, most people prefer to draw from Urn 2, which implies that $p(B_2) > p(B_1)$. The overall pattern of choices within and between urns leads to the following,

$$p(R_2) > p(R_1) = .5 \text{ and } p(B_2) > p(B_1) = .5; \textit{ or,}$$
$$p(R_2) = .5 > p(R_1) \text{ and } p(B_2) = .5 > p(B_1)$$

In the first case, the sum of $p(R_2)$ and $P(B_2)$ is greater than one (hereafter called "superadditivity"); in the second case, the sum of $p(R_1)$ and $p(B_1)$ is less than one (hereafter called "subadditivity"). Thus, either Urn 2 has complementary probabilities that sum to more than one, or Urn 1 has complementary probabilities that sum to less than one. As we will show, the nonadditivity of complementary probabilities is central to judgments under ambiguity.

Ellsberg's paradox demonstrates that although it may seem strange and awkward to speak of uncertainty as being more or less certain itself, such a concept is crucial for understanding how people make judgments and decisions in their natural environment. In fact, the notion of uncertainty about uncertainty has been discussed under a variety of rubrics; e.g., ambiguous probabilities, second-order uncertainty, and probabilities-for-probabilities (e.g., Marschak, 1975). Moreover, current work on fuzzy sets (Zadeh, 1978), Shafer's (1976) theory of evidence, Cohen's (1977) attempt to formalize uncertainty in legal settings, and the elicitation of probability ranges (Wallsten, Forsyth, & Budescu, 1983), all contain ideas regarding the vagueness that can underlie probabilities. However, it should be noted that the concept of ambiguous probabilities has not received universal acceptance (e.g., de Finetti, 1977; also see the various responses to Ellsberg's original article – Roberts, 1963; Raiffa, 1961; Ellsberg, 1963). Be that as it may, empirical evidence (e.g., Becker & Brownson, 1964; Curley & Yates, 1985; Gärdenfors & Sahlin, 1982; Yates & Zukowski, 1976) has shown that ambiguity affects judgments and choices and should not, therefore, be ignored. However, it is one thing to acknowledge the importance of ambiguity (cf. Keynes, 1921, p.71; Knight, 1921) and another to develop a theory that incorporates it in the assessment of probabilities

and the determination of choices. Before turning to that task, we need to define the concept of ambiguity more precisely.

Reconsider Urn 1 (unknown proportion) in Ellsberg's problem and note that all probability distributions over the proportions of red and black are equally likely. Now imagine that one samples four balls (without replacement) and gets 3 reds and 1 black. The proportion of red is now restricted to .03 + x (where $0 \leq x \leq .96$) and the proportion of black to .97 - x. This result rules out certain probability distributions, thereby making others more likely. Indeed, as sample size increases, further distributions are ruled out until only one is left. We can now distinguish between ignorance, ambiguity, and risk according to the degree to which one can rule out alternative distributions; that is, ambiguity is an intermediate state between ignorance (no distributions are ruled out) and risk (all but one distribution is ruled out). Thus, ambiguity results from the uncertainty associated with specifying which of a set of distributions is appropriate in a given situation. Moreover, the amount of ambiguity is an increasing function of the number of distributions that are not ruled out by one's knowledge of the situation.

As pointed out by Ellsberg (1961), various factors can affect ambiguity in addition to the amount of information (such as sample size). For example, ambiguity will generally be high when evidence is unreliable and conflicting, or the causal process generating outcomes is poorly understood. On the other hand, well-known random processes (such as flipping coins or dice) are uncertain but not ambiguous since the probabilities are well specified. The following example, given by Gärdenfors and Sahlin (1982), is useful in distinguishing between uncertainty, ignorance, and ambiguity.

> Consider Miss Julie who is invited to bet on the outcome of three different tennis matches. As regards match A, she is very well-informed about the two players. . . . Miss Julie predicts that it will be a very even match and a mere chance will determine the winner. In match B she knows nothing whatsoever about the relative strength of the contestants . . . Match C is similar to match B except that Miss Julie has happened to hear that one of the contestants is an excellent tennis player although she does not know anything about which player it is, and that the second player is indeed an amateur so that everyone considers the outcome of the match a foregone conclusion. (pp. 361-362)

We argue that match A is uncertain but not ambiguous (analogous to Urn 2 in Ellsberg's paradox), match B reflects ignorance (analogous to Ellsberg's Urn 1 since all distributions over the probability of winning are equally likely), and match C is ambiguous since the probability of each player winning is either 0 or 1.

Ellsberg's paradox demonstrates ambiguity avoidance since people prefer to draw from the unambiguous urn. Indeed, Ellsberg (1961, p. 666) stated that ambiguity avoidance helps to explain why new technologies are resisted more than one would expect on the basis of their first-order probabilities of accidents, failures, and so on. However, are there conditions under which ambiguity will be sought rather than avoided ? Another Ellsberg example (quoted in Becker & Brownson, 1964, pp. 63-64, Footnote 4), illustrates ambiguity preference: Consider two urns with 1000 balls each. In Urn 1, each ball is numbered from 1 to 1000, and the probability of drawing any number is .001. In Urn 2, there are an unknown number of balls bearing any single number. For example, the proportion of balls bearing number 687 could vary from 0 to 1. If there is a prize for drawing number 687 from the urn, would you prefer to draw from Urn 1 or Urn 2 ? Urn 1 contains no ambiguity since the probability of winning is exactly .001; Urn 2 involves ignorance since all probabilities of winning are equally likely. For many people, Urn 2 seems a more attractive bet than Urn 1. Hence, there are situations in which ambiguity is preferred rather than avoided. We consider this in more detail in the next section but note that accounting for such shifts in "attitudes toward ambiguity" is an important criterion for judging the adequacy of any theory of ambiguity.

The Ambiguity Model

We now develop a model of how people assess uncertainty in ambiguous situations. To judge the adequacy of our model, we establish the following criteria: (1) The model must be able to explain the pattern of choices in Ellsberg's paradox. This means that the model should allow for sub- *and* superadditivity of complementary probabilities; (2) The model should specify the conditions under which people will avoid or seek ambiguity; (3) Individual differences should be captured by different parameter values within the same general model; (4) The model should be empirically testable and falsifiable.

Anchoring-and-Adjustment Strategy

The basic idea underlying the ambiguity model is that people use an anchoring-and-adjustment strategy in which an initial probability is used as the anchor (or starting point), and adjustments are made for ambiguity. The anchor probability can come from a variety of sources; it may be a probability that is salient in memory, the best guess of experts, or a probability that is otherwise available. Denote the anchor probability as p and the judged probability that results from the anchoring-and-adjustment process as S(p). Thus,

$$S(p) = p + k \tag{1}$$

where k is defined as the net effect of the adjustment process. The adjustment process is assumed to involve a mental simulation in which higher and lower values of p are imagined. The rationale for this is that since p can come from any one of a number of distributions, the imagining of different values allows one to evaluate which of these distributions is more or less plausible. For example, in assessing the probability of a defect in a new type of computer chip, one may have an estimate from the engineering department that is based on meager data. One could then "try out" other values of p to see if they are "in the ballpark." Once values of p are imagined and evaluated, they are incorporated into the adjustment term, thereby allowing one to maintain sensitivity to both uncertainty and ambiguity.

To model the net effect of the mental simulation process, k is assumed to be a function of three factors:

(1) Level of the anchor, p – since $0 \leq S(p) \leq 1$, k must lie in the interval, $-p \leq k \leq 1-p$. This means that the sign of the adjustment must be partly due to the size of the anchor. Indeed, if $p = 1$, k must be negative (or zero) and the adjustment will be downwards; similarly, if $p = 0$, k will be positive (or zero) and the adjustment will be upwards. When $0 < p < 1$, adjustments can be either up or down.

(2) Amount of ambiguity – the greater the amount of ambiguity, the larger the size of the simulation (the bigger the ballpark). In the limiting case of no ambiguity, a mental simulation process is

unnecessary since the value of p is exactly known. In the case of ignorance, ambiguity is at its maximum and all values of p are equally plausible. We denote the parameter θ as the amount of ambiguity in the situation ($0 \leq \theta \leq 1$).

(3) Attitude toward ambiguity – this refers to the relative weighting of (imagined) probabilities that are higher and lower than the anchor. We denote β as a parameter reflecting this relative weighting ($\beta \geq 0$). Note that one's attitude toward ambiguity is crucial in determining whether one adjusts upwards or downwards. For example, if one gives more weight to higher probabilities than lower ones, this generally results in upward adjustments to the anchor. On the other hand, if one gives more weight to lower probabilities, downwards adjustments are more likely. The sign of k is thus determined by β and p.

To model the adjustment process, let

$$k = k_g - k_s \tag{2}$$

where k_g denotes the effect of imagining values of p *greater* than the anchor, and k_s the effect of imagining *smaller* values. Note that the maximum values of k_g and k_s are (1 - p) and p, respectively (since $-p \leq k \leq 1-p$). However, the size of the simulation depends on the amount of ambiguity, θ. We assume that k_g and k_s can be represented as proportions of the maximum adjustments where θ is the constant of proportionality; that is,

$$\begin{aligned} k_g &= \theta\,(1 - p) \\ k_s &= \theta\, p \end{aligned} \tag{3}$$

Note that under no ambiguity, $\theta = 0$, $k = 0$, and $S(p) = p$ for all p. Thus, adjustments to the anchor only occur under ambiguity.

Now consider one's attitude toward ambiguity, β. Since β represents the relative weighting of higher versus lower probabilities, we need only weight either k_g or k_s to affect k. For convenience, we weight k_s by β as follows:

$$k_s = \theta\, p^{\beta} \tag{4}$$

By substituting (3) and (4) into (2), the net effect of the adjustment for ambiguity (k) is given by,

$$k = \theta\,(1 - p - p^{\beta}) \tag{5}$$

When Equation 5 is substituted into Equation 1, the full model becomes,

$$S(p) = p + \theta\,(1 - p - p^{\beta}) \tag{6}$$

Note that the full model can also be expressed as,

$$S(p) = (1 - \theta)\,p + \theta\,(1 - p^{\beta}) \tag{7}$$

Equation 7 implies that the judged ambiguous probability is a weighted average of p and $(1 - p^{\beta})$, where the weights reflect the amount of ambiguity, θ.

Implications of the model. Although the ambiguity model is derived from a small number of psychological assumptions, it is nevertheless rich in implications. We now consider these in some detail.

(1) The ambiguity model implies that S(p) is regressive with respect to p. This can best be seen in Figure 1, which shows S(p) as a function of p for different values of β, holding θ constant ($\theta > 0$).

....

Insert Figure 1 about here

....

In panel (a), $0 < \beta < 1$, which implies that probabilities lower than the anchor are weighted more heavily than those above the anchor. This leads to downward adjustments (i.e., $k < 0$) over most of the range of p; hence, $S(p) < p$. However, it is important to note that β defines a "cross-over" point

(denoted p_c) where $S(p) = p$. When $p < p_c$, $S(p) > p$ even though lower probabilities in the mental simulation receive more weight than higher ones. Why does this occur? Recall that the sign of the adjustment is determined by β *and* the level of p. For example, when p is small, there are fewer lower probabilities to imagine and thus the net effect of the adjustment process is positive.

In panel (b), $\beta > 1$, which implies that probabilities higher than the anchor are weighted more than lower ones. This results in upward adjustments over much of the range of p; hence, $S(p) > p$ when $p < p_c$. On the other hand, when $p > p_c$, the greater weight for imagined higher probabilities does not compensate for their reduced number and $S(p) < p$. Now consider panel (c), where $\beta = 1$. This implies that higher and lower probabilities are equally weighted in the simulation process; hence, $S(p) = p$ at .5.

(2) Equation 6 specifies the conditions under which judgments of complementary probabilities are additive (sum to one). Specificially,

$$S(p) + S(1 - p) = 1 + \theta [1 - p^{\beta} - (1 - p)^{\beta}] \qquad (8)$$

There are three sufficient conditions for additivity: (a) no ambiguity ($\theta = 0$); (b) equal weighting of imagined probabilities ($\beta = 1$); and (c) the anchor probability expresses either certainty or impossibility ($p = 0,1$). Otherwise, $\beta < 1$ implies subadditivity (shown in panel (a)), and $\beta > 1$ implies superadditivity (shown in panel (b)).

(3) Ellsberg's paradox and individual differences – we now discuss how the ambiguity model explains the various patterns of responses to Ellsberg's paradox. First, consider someone with parameter values as shown in panel (a); i.e., $\theta > 0$ and $0 < \beta < 1$. In decisions under ambiguity, such a person will effectively underweight $p > p_c$, and overweight $p < p_c$, thereby generating the typical pattern of responses in Ellsberg's original problem. According to our model, most people choose the nonambiguous urn when $p = .5$ because $S(p = .5) < .5$. Such a choice seems to reflect "ambiguity avoidance." However, the same person who chooses the unambiguous urn when $p = .5$ often chooses the ambiguous urn when $p = .001$. From our perspective, if $p = .001$ is less than the cross-over point (p_c), $S(p = .001) > .001$ and "ambiguity seeking" at low probabilities is perfectly

consistent with ambiguity avoidance at moderate to high probabilities (for positive payoffs). This also explains some otherwise puzzling results in which lotteries with low but unreliable probabilities are chosen over those with equally low and reliable probabilities (Gärdenfors & Sahlin, 1982).

The ambiguity function shown in panel (a) of Figure 1 does not explain why some people in the Ellsberg task prefer to choose the ambiguous urn when $p = .5$ (see the next section for empirical evidence). However, consider a person with parameter values as shown in panel (b); i.e., $\theta > 0$ and $\beta > 1$. In this case, $S(p = .5) > .5$, which is consistent with ambiguity seeking in Ellsberg's original problem. Because individual differences are rarely considered in decision making under uncertainty, our model has the distinct advantage of positing a general process, yet allows for individual variations via different parameter values.This is illustrated by considering people who are indifferent between ambiguous and nonambiguous urns at $p = .5$. Our model distinguishes between two types; those for whom $\theta = 0$ and, those with parameters values as shown in panel (c) (i.e., $\theta > 0$, $\beta = 1$). This latter group does not adjust at $p = .5$ but does adjust at all other values of p. Hence, these people will only be indifferent between lotteries at $p = .5$.

(4) Dynamic ambiguity – the ambiguity model presented here is static; it gives an account of judgment under ambiguity at a given point in time. However, what happens as more information is obtained? In the simple case where new information reduces ambiguity without changing the anchor probability (i.e., new data increases the absolute amount of information without changing the relative balance of positive and negative evidence), our model can be extended as follows: let ν denote the amount of new information acquired in time period t. Furthermore, let the judged ambiguous probability after time period t, $S(p)_t$, be written as,

$$S(p)_t = p + (\theta/\nu)\,(1 - p - p^{\beta}) \tag{9}$$

Therefore, as ν increases, the effect of ambiguity on the adjustment process decreases. Indeed, as ν gets very large, $S(p)_t$ approaches p. This also means that complementary probabilities will approach additivity as ν increases since,

$$S(p)_t + S(1\text{-}p)_t = 1 + (\theta/\nu)\,[\,1 - p^{\beta} - (1 - p)^{\beta}\,] \tag{10}$$

(5) The version of the ambiguity model shown in panel (a) bears a striking resemblance to the decision weight function of prospect theory (Kahneman & Tversky, 1979). In that theory, the effects of uncertainty on choice are modeled via a decision weight function, $\pi(p)$, that is subadditive, has undefined end points, and displays "subproportionality". This latter characteristic implies that the slope of the decision weight function is less than 1 for all p (i.e., $\pi(p)$ is flatter than the diagonal). These characteristics, together with a value function defined on gains and losses, accounts for many choice paradoxes. Since prospect theory concerns gambles with well-defined probabilities, its domain is different from ours. Nevertheless, we believe that the similarity in representing how uncertainty affects choice is not coincidental (see Discussion section).

(6) We have implicitly assumed that the parameters θ and β are such that S(p) is monotone increasing with p. However, the function shown in Equation 6 is sufficiently flexible so that nonmonotone as well as decreasing monotone functions are possible. In fact, we have found some evidence for nonmonotonicity in studies fitting the θ and β parameters to probability judgments under ambiguity (Einhorn & Hogarth, 1985). Moreover, a situation in which S(p) is likely to be a decreasing function of p arises when the surface meaning of data suggests the opposite conclusion; for example, imagine someone who "protesteth too much," or a suspect who is "framed" for a crime. If we denote θ^* as reflecting the credibility of the data (where higher values of θ^* mean lower credibility), then lack of credibility ($\theta^* = 1$) implies that,

$$S(p) = 1 - p^{\beta} \tag{11}$$

Thus, as p increases, S(p) decreases. More generally, as θ^* increases, it reaches a point, conditional on p and β, where the data for a hypothesis starts to count against it.

Empirical Evidence

The ambiguity model can be tested in a variety of ways. Three studies are presented that

investigate (a) variations of the Ellsberg paradox; and (b) implications of the model for buyers and sellers of insurance and a warranty (Einhorn & Hogarth, 1985; Hogarth & Kunreuther, 1985a, 1985b).

Ellsberg Revisited

The ambiguity model predicts both ambiguity seeking and avoidance, depending on p, the size of the anchor probability, and β, one's attitude toward ambiguity. To examine this, first consider choices involving positive payoffs. Recall that in the original version of the paradox, people are offered a $100 payoff if they choose a specified colored ball drawn from one of the urns. The basic result is that most people prefer to draw from the unambiguous urn, indicating ambiguity avoidance. However, if the probability of winning is small, Ellsberg conjectured that people would prefer to draw from the ambiguous urn, thereby displaying ambiguity seeking. To our knowledge, this latter hypothesis has not been put to an empirical test. Since the ambiguity model can predict both ambiguity avoidance for $p = .5$ and ambiguity seeking for low probabilities (see Figure 1, panel (a)), a simple choice experiment that varies the probability of winning should provide evidence on Ellsberg's conjecture as well as the adequacy of the model.

In addition to varying the probabilities in Ellsberg's paradox, we investigated whether attitudes toward ambiguity change when negative, rather than positive payoffs, are involved. This is important since loss gambles with ambiguous probabilities are quite common, especially in insurance (see next section for empirical evidence). Moreover, the simulation process underlying our model can be taken to imply that the assessment of ambiguous probabilities will result in a differently shaped function for losses as opposed to wins. To see this, assume that people are generally cautious in assessing uncertain probabilities. When assessing loss probabilities, they should therefore give more weight to higher values of the (simulated) loss probabilities than to lower values. This will result in an overestimation of loss probabilities, especially in the low to moderate range. Note that the overestimation of ambiguous loss probabilties *and* the underestimation of ambiguous win probabilities are both consistent with a general conservative attitude toward ambiguity. We now turn to a test of these ideas.

Experimental design and results. There were two tasks in which subjects were asked to choose (or express indifference) between drawing a specified type of ball from either an ambiguous or nonambiguous urn. In the first task, subjects were asked to imagine two urns each containing 100 balls. They were further told that half of the balls in one urn were red and half black (the unambiguous case), but they were not informed as to the proportions of red and black balls in the second urn (the ambiguous case). The payoff was contingent on drawing a ball of a specified color (red or black). In the second task, subjects were asked to imagine two urns each containing 1000 balls. In the nonambiguous urn, the balls were numbered consecutively from 1 to 1000 and subjects were told that the payoff was contingent on drawing ball number 687 ($p = .001$). In the ambiguous case, subjects were told that any proportion of the 1000 balls could be number 687.

Thus, the first task involved choosing (or expressing indifference) between an ambiguous or nonambiguous urn where the probability of the payoff was known to be .5 for the latter urn. The second task was similar in structure except that the probability of the payoff in the nonambiguous case was .001. The study investigated the effects of positive and negative payoffs by asking subjects to imagine prizes or penalties of $100. All subjects responded to both tasks but were randomly allocated to two groups. In one group, subjects were given the first task ($p=.5$) with a positive payoff and the second ($p=.001$) with a negative payoff. In the second group, this manipulation was reversed (i.e., negative payoff at .5 and positive payoff at .001).

The subjects were 274 MBA students at the University of Chicago who responded to questionnaires distributed at the beginning of a course on decision making.

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Insert Table 1 about here

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The main results are shown in Table 1. First, consider the results for positive payoffs when the choice is between an urn with known $p = .5$ and an ambiguous urn. The modal response (47%) favors the nonambiguous urn, thereby supporting Ellsberg's hypothesis of ambiguity avoidance. However, a considerable proportion exhibits indifference (34%), (perhaps reflecting business school training), and a surprising 19% of subjects are ambiguity seeking. Now consider the choice pattern

when the known probability is small ($p = .001$). Although the modal response still favors the nonambiguous urn (43%), the choice of the ambiguous urn increases from 19% to 35%. Next, consider the results for negative payoffs when $p = .5$. The modal response is now indifference (56%) and ambiguity seeking is sharply reduced to 14%. Futhermore, when $p = .001$, ambiguity seeking is further reduced (to 5%) and the modal response shifts to strong ambiguity avoidance (75%). Hence, there are large differences in responses to ambiguity between gambles with positive and negative payoffs.

In terms of the ambiguity model, the overall pattern of results can be summarized by referring back to panels (a) and (c) in Figure 1. Note that panel (a) shows an ambiguity function that is consistent with the experimental results for positive payoffs. Thus, there is ambiguity avoidance for $p = .5$ but ambiguity preference for $p = .001$. The shape of the ambiguity function for negative payoffs is consistent with panel (c). In this case, loss probabilities are overestimated until $p = .5$ (at which point $S(p) = p$), but underestimated when $p > .5$. This latter prediction was not explictly tested in this study but is investigated below.

Insurance

The buying and selling of insurance provides an important context to test the ambiguity model for two reasons: (1) Buyers and sellers often have different amounts of information concerning the probability of the event to be insured. Thus, they may not experience the same amount of ambiguity in assessing the occurrence of a potential loss; (2) Buyers of insurance are trying to transfer their risk and are willing to pay a premium (thus suffering a sure loss) to do so. On the other hand, sellers of insurance are taking on a risk in the belief that the probability of losing the bet with the buyer is in their favor. In terms of the simulation process underlying our model, we hypothesize that sellers will give *more* weight than buyers to the higher simulated loss probabilities. The rationale for this is based on the greater cost to the seller of underestimating loss probabilities. Note that the buyer may also overestimate the probability of loss by weighting higher loss probabilities more than lower ones, but our hypothesis concerns the comparison between buyers and sellers. In fact, there is some empirical evidence consistent with the notion that the person who assumes a risk gives more attention to higher

values of the loss probability than someone who transfers the risk (Hershey, Kunreuther, and Schoemaker, 1982; Thaler, 1980). In terms of our model, the above hypothesis implies that, $\beta_{seller} > \beta_{buyer}$.

In order to explicate how these differences can be captured by our model, consider Figure 2,

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Insert Figure 2 about here

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which shows a simplified 2x2 classification of buyers and sellers in either an ambiguous or nonambiguous state. In cell 1, buyers and sellers are well acquainted with the probabilities of the potential loss and are thus in a nonambiguous state. In this case, $\theta = 0$ and $S(p) = p$ for both buyers and sellers. If it is assumed that selling and buying prices for insurance are the same monotonic function of S(p), then we predict that buyers and sellers should have the same buying and selling prices for insurance over the full range of loss probabilities. Thus, we expect that the sellers' premiums will be equal to the prices buyers are willing to pay. Now consider the more typical case shown in cell 2, in which the seller is not ambiguous (due to actuarial data, for example), but the buyer is. In this situation, $\theta = 0$ and $S(p) = p$ for the seller; however, the ambiguous buyer will overestimate most of the loss probabilities, $S(p) > p$, until the ambiguity function crosses the diagonal, after which $S(p) < p$. We therefore predict that the buyer will be willing to pay more for insurance than the seller asks at small and even moderate values of p. However, above some value of p, the buyer will not be willing to pay the premium asked by the seller.

The situation shown in cell 3 is less likely although one example may be the case of new technologies in which inside information is available to the buyers (e.g., owners of the new companies) but not to the sellers. In any event, we predict that sellers will overestimate the loss probabilities over most of the range of p (i.e., $S(p) > p$), while $S(p) = p$ for the buyers. This implies that for most probabilities, sellers will set premiums that are higher than buying prices. Finally, consider cell 4, which shows the situation where buyers and sellers are both ambiguous, and assume that $\theta_{seller} = \theta_{buyer}$. According to our argument, if $\beta_{seller} > \beta_{buyer}$, then $S(p)_{seller} > S(p)_{buyer}$ over the full range of p. Hence, we predict that the sellers' premiums will be higher than buying

prices for all loss probabilities.

The four predictions that follow from the ambiguity model are summarized in Figure 3 which shows the implied ambiguity functions for buyers and sellers under both ambiguous and

Insert Figure 3 about here

nonambiguous conditions. Prediction 1 states that buyers and sellers will have equal prices when they are both nonambiguous; i.e., $S(p) = p$ for both buyers and sellers. Prediction 2 concerns nonambiguous sellers and ambiguous buyers. Note that the buyers should be willing to pay more for insurance than the sellers ask, up to the point where $S(p) = p$; after this point, buyers should be unwilling to pay what sellers ask. Prediction 3 concerns ambiguous sellers and non-ambiguous buyers. In this case, sellers' premiums should be larger than buying prices over most of the range of p. Finally, Prediction 4 concerns the case when buyers and sellers are both ambiguous. This situation results in premiums that are higher than buying prices over the whole range of loss probabilities.

Experimental design and results. Prices for insurance were investigated for ambiguous and nonambiguous loss probabilities of .01, .35, .65, and .90. Subjects were given a scenario in which the owner of a small business with assets of $110,000 was seeking to insure against a possible $100,000 loss. The probability of the loss (due to a defective product) was given at one of the four levels in both the ambiguous and nonambiguous conditions. However, a comment was added as to whether one could "feel confident" (nonambiguous case) or "experience considerable uncertainty" (ambiguous case) concerning the estimate. In addition, half the subjects were told that they were sellers of insurance and the other half were assigned the role of buyers. The sellers were asked to imagine they headed a department in an insurance company and were authorized to set premiums. The buyers were told to imagine that they were the owner of the company. As far as possible, the same wording was used in both the buyer and seller versions of the scenario. After reading the scenario, subjects were asked to state maximum buying prices (for buyers) or minimum selling prices (for sellers).

The experimental design involved having different subjects as buyers or sellers at each of the

four probability levels. Thus, there were 8 different groups of subjects (2x4). Each subject was given both the ambiguous and nonambiguous version of the scenario. Therefore, the design involved a within subjects factor (ambiguity/nonambiguity) and two between subjects factors (probability levels and buyer versus seller). The subjects were 112 MBA students at the University of Chicago. These subjects had prior training in business, economics, and statistics, and the insurance context was familiar to them.

The basic results are shown in Table 2, which shows the median prices for all experimental conditions (medians are reported since several distributions within conditions are quite skewed).

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Insert Table 2 about here

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Our first prediction concerns columns (1) and (3), buyers and sellers nonambiguous. We predicted that the prices would be equal for buyers and sellers and the results support the prediction. The second prediction concerns columns (2) and (3), buyers ambiguous and sellers nonambiguous. Note that the buyers are willing to pay more for insurance than the sellers ask at $p = .01$ ($1500 vs. $1000), but the prices are (approximately) equal at $p = .35$; thereafter, the buying price is less than the seller's asking price. This pattern is exactly predicted by our model. The third prediction concerns columns (1) and (4), nonambiguous buyer and ambiguous seller. Here the seller's price is higher than the buyer's over the range of p, in accord with our prediction. However, our model also implies that at very high p, the seller's price should be lower than the buyers and this is not observed in these data. On the other hand, the ratio of premiums to buying prices decreases as p increases, which does accord with our model. Finally, consider our fourth prediction, which involves columns (2) and (4), buyer and seller both ambiguous. As predicted, the seller's price is higher than the buyers for all values of p. In Hogarth and Kunreuther (1985a; 1985b), the results of several related experiments are reported using different scenarios, research designs, subjects, and response modes. The results of those experiments are consistent with the findings reported here.

Warranty Pricing

A warranty is a particular type of insurance contract in which the seller agrees to fix, replace, or otherwise make good, the product sold to the buyer. The buyer, in turn, agrees to pay a premium for the warranty (we assume that products sold with warranties have the premium incorporated into the price of the product). The purpose of the present study was to test the ambiguity model in the context of buying and selling a warranty. In addition, the subjects in the experiment were executives in life insurance companies rather than business students. This gave us a chance to see whether our previous results would replicate in a different context and with a more sophisticated and knowledgeable subject population.

Experimental design and results. The subjects were 136 executives in life insurance companies attending a management seminar. They completed a questionnaire given to them the evening before the seminar began. The question of interest for this study involved a scenario describing a new personal computer that was about to be distributed by the owner of a computer store. The probability of a defect in the computer requiring repair was given as .05, .25, or .75. In the ambiguous probability condition, it was stated that there was little experience with the actual use of the computer and that there was considerable disagreement among experts concerning the probability of a defect. In the nonambiguous condition, it was stated that there was considerable testing of the computer and one could be confident in the estimated defect probabilities upon which all experts agreed. Half the subjects were assigned to the ambiguous condition and the other half to the nonambiguous condition. In addition, for each of these groups, subjects were further divided into buyers (i.e., consumers) or sellers (computer store owners). The sellers were asked to set a minimum price for the warranty on the computer; the buyers were asked to state the maximum price they would pay for a warranty. The cost of fixing the defect was stated to be $400. To summarize, the design of the study involved four separate groups depending on whether subjects were buyers or sellers, and whether the probabilities were ambiguous or not. Furthermore, each subject was asked to state either a buying or selling price for each of the three probability levels. Thus, probability levels were varied as a within subject factor.

The median prices for all experimental conditions are shown in Table 3.

Insert Table 3 about here

We discuss these results in terms of the four predictions made in the insurance study. First, when buyers and sellers are non-ambiguous (columns (1) and (3)), premiums and buying prices should be equal. This holds for p = .05, approximately so for p = .25, but not for p = .75. Second, when buyers are ambiguous and sellers are unambiguous (columns (2) and (3)), our model predicts that buyers are willing to pay more than sellers ask at low probabilities, but less than sellers ask for moderate to high probabilities. This pattern is supported by the data. Third, when buyers are nonambiguous and sellers are ambiguous (columns (1) and (4)), the model predicts that premiums will be higher than buying prices over most of the range of p. Note that this is indeed the case. However, as was the case in the insurance study, we do not find that the buyer's price is above the seller's at very high probabilities. Fourth, when buyers and sellers are both ambiguous (columns (2) and (4)), we predict that the seller's price will be higher than the buying price over the whole range of p. As can be seen, this is the case. Taken together, these findings essentially replicate the results from the insurance study.

Although we have presented three experiments testing the implications of the ambiguity model, the interested reader is referred to further experiments in Einhorn and Hogarth (1985). These concern the fitting of θ and β parameters to individual subjects' probability judgments, the prediction of sub- and superadditivity of complementary probabilities, and the prediction of choices based on the fit of the model to probability judgments. In general, the results of these studies are consistent with the implications from the model.

Discussion

We first consider our theoretical and empirical results with regard to choice under ambiguity. Thereafter, we discuss possible extensions of the model to the case where probabilities are not ambiguous.

Our model for assessing ambiguous probabilities can be extended in a straightforward way to

include an explicit decision rule for choice under ambiguity. We first assume, in accord with prospect theory (Kahneman & Tversky, 1979), that the subjective worths of outcomes are defined over gains and losses rather than final asset positions. Denote w_G and w_L as the subjective worths of the amounts to be gained and lost in a two-outcome gamble, respectively. We then define the concept of *expected worth under ambiguity* (EWA) as,

$$EWA = w_G \, S(p_G) + w_L \, S(p_L) \tag{12}$$

where, $S(p_G)$ and $S(p_L)$ are the ambiguous probabilities of gaining and losing. Moreover, we assume that people choose amongst ambiguous gambles in accord with EWA; that is, one chooses to maximize EWA. We make several points with respect to the rule embodied in (12): (a) Under no ambiguity, $S(p_W) = p_W$, $S(p_L) = p_L$, and EWA is equivalent to the expected utility model (except that subjective worths are defined over gains and losses); (b) Although our model implies that S(p) can be both nonmonotonic and negatively related to p (depending on the values of θ and β), we restrict these parameters in choice under ambiguity (and uncertainty, see below) so that S(p) is always an increasing function of p. To do otherwise would permit violations of dominance. However, we do permit violations of dominance to occur in judgments. Indeed, some evidence for this has been found by Goldstein and Einhorn (1986), using minimum selling price judgments for gambles. Since judgment and choice may not be psychologically equivalent (Einhorn & Hogarth, 1981; Slovic, Fischhoff, & Lichtenstein, 1982), the distinction between the ambiguity model for judgment and the EWA model for choice is not unreasonable; (c) We are aware of only two other rules for dealing with ambiguous choice; one due to Ellsberg (1961, pp. 664-669) and the other to Gärdenfors and Sahlin (1982). However, neither of these rules allows for ambiguity seeking *and* avoidance. Moreover, these rules do not imply different ambiguity functions for gains and losses. On the other hand, Equation (12) does account for ambiguity seeking and avoidance for both gains and losses. Recall that in Experiment 1, the results for the $100 payoff showed ambiguity avoidance at $p_G = .5$, but considerable ambiguity preference at $p_G = .001$. If the ambiguity function for gains is as shown in panel (a) of Figure 1, it follows from (12) that,

$$w(\$100)\ S(p_G = .5) < w(\$100)\ (.5) \text{ and,}$$

$$w(\$100)\ S(p_G = .001) > w(\$100)\ (.001)$$

Hence, there is ambiguity avoidance at moderate to high gain probabilities and ambiguity preference at low gain probabilities. It is possible, with appropriate values of θ and β, to account for other patterns of choice. In particular, since many people in Experiment 1 chose to avoid the ambiguous urn at $p_G = .001$, β could be made smaller so that it crosses the diagonal at a p_G value less than .001. We believe that $S(p_G)$ will eventually cross the diagonal at some point because otherwise a person would prefer a sure probability of no gain (i.e., $p_G = 0$) to an ambiguous probability of no gain, $S(p_G = 0)$. Because the latter offers some non-zero chance of a gain as opposed to no chance, we would expect ambiguity seeking to occur below some value of p_G.

Now consider the choices under ambiguity for the loss payoff in Experiment 1. Recall that in this case, when $p_L = .5$, indifference between the urns was the largest response; when $p_L = .001$, ambiguity avoidance was the overwhelming response. This pattern implies that,

$$w(-\$100)\ S(p_L = .5) = w(-\$100)\ (.5) \text{ and,}$$

$$w(-\$100)\ S(p_L = .001) < w(-\$100)\ (.001)$$

This pattern is consistent with an ambiguity function for losses such as that shown in panel (c) of Figure 1. Note that this function also implies ambiguity seeking for losses when $p_L > .5$; i.e., $S(p_L) < p_L$ for $p_L > .5$. Reasoning in a manner analogous to the case for gains, we believe that ambiguity seeking will occur for some (high) loss probabilities otherwise a sure loss ($p_L = 1$) would be preferred to an ambiguous loss, $S(p_L = 1)$. It is an empirical question as to what the cross-over point will be in any particular situation.

An interesting aspect of our model is that it implies a lack of independence between ambiguous probabilities and the sign of utilities; i.e., different ambiguity functions depend on whether one is dealing with gains or losses. Furthermore, since we have asssumed that $\beta_{gain} < \beta_{loss}$, choices under ambiguity that deal with pure gain gambles are likely to imply subadditivity of complementary probabilities ($\beta_G < 1$), while those dealing with pure loss gambles should lead to less subadditivity, including additivity ($\beta_L = 1$) and even superadditivity ($\beta_L > 1$). While more data are needed to test this hypothesis, it suggests the need for a "dual probability function" in choices under ambiguity (cf.

Irwin, 1953; Luce & Narens, 1985; Marks, 1951; Nygren & Isen, 1985). In fact, Edwards (1962) commented on the nonindependence of the sign of utilities and probabilities some 25 years ago;

> All of these findings strongly indicate that there is at least an interaction between the *sign* of the utility of a bet and the subjective probability associated with the event ...Furthermore, the direction of the effects is in general the direction predicted by the Irwin subjective probability theory. None of the evidence, however, indicates an interaction between value and subjective probability provided that the signs of the utilities involved do not change. (pp.45-46)

Our results regarding buying and selling prices for insurance and a warranty (Experiments 2 and 3) raise the important question as to how one's "perspective" influences the assessment of ambiguous uncertainties. For example, consider the difference between those who live near the site of a planned nuclear power plant and the nuclear engineers who are designing it. The former may experience a great deal of ambiguity about the probability of an accident and greatly overestimate this relative to the engineers' "best guess." The importance of perspective can also be seen in situations where the participants to a dispute code the outcomes in terms of gains versus losses. For example, consider a defendant and plaintiff in a lawsuit where the lawyers for both sides estimate the probability of winning as .5 but neither side is confident in the estimate. From the plaintiff's point of view, one needs to assess the ambiguous probability of a gain, $S(p_G)$; from the defendant's point of view, one needs to assess the ambiguous probability of a loss, $S(p_L)$. If these two functions are not the same (as we have argued), the relative sizes of β_L and β_G will determine whether both sides are overconfident, underconfident (and thus settle out of court), or one side wishes to settle but the other refuses. According to our analysis, we expect that in general, $\beta_G < \beta_L$, reflecting cautious attitudes and thus underconfidence by both parties. This implies that most lawsuits will be settled out of court, as indeed occurs in 95% of cases (see, Gould, 1973, where an expected utility analysis assuming known probabilities is also consistent with this evidence). While the decision to go to trial or settle out of court is more complicated than indicated by our present discussion, our purpose is to emphasize that one's perspective can affect the assessment of ambiguous probabilities and the decisions on which they are based.

Extension to known probabilities. The simulation process underlying the assessment of ambiguous probabilities provides a plausible psychological mechanism to account for probability "weights" that differ from stated probabilities in descriptive theories of risk. To see how such weights can result from a simulation process when probabilities are explictly given, an auxiliary process must be hypothesized that accounts for imagining and differentially weighting higher and lower values of the stated probabilities. Imagine that the size of a payoff, like the size of a planet, exerts a gravitational force on those objects or factors (such as uncertainties) that are associated with it. The effect of this "force" could be modeled via the simulation process (including optimistic or pessimistic attitudes captured by different values of β) such that decision weights would differ from stated probabilities. If this were the case, utilities and probabilities would not only be sign dependent (as discussed before), but size dependent as well. In fact, evidence for size dependence has been found by Wothke (1985) and Hogarth & Einhorn (in preparation). For example, choices in many well-known utility theory paradoxes (e.g., Allais, 1953) are not paradoxical vis-à-vis utility theory when payoffs are small as opposed to large.

If one equates choices that are consistent with utility theory as reflecting "rationality" (cf. Einhorn & Hogarth, 1981), there is considerable irony in the fact that in these cases large incentives produce less rational choice than small incentives. On the other hand, such results are consistent with evidence showing that the relation between performance and motivation (which we equate with incentive size) is single-peaked (e.g., Yerkes & Dodson, 1908). Hence, there is often an optimal amount of motivation beyond which performance declines. Performance, however, depends on both cognition and motivation. Thus, if incentive size can be thought of as analogous to the speed with which one travels in a given direction, cognition determines the direction. Therefore, if incentives are high but cognition is faulty, one gets to the wrong place faster. Clearly, much remains to be done in explicating the relations between incentive size, the assessment of uncertainty, and the effects of both on choice.

In addition to the effects of size and sign of payoff on probabilities, the simulation process suggests that changes in the β parameter can be used to model context effects in the choice process. For example, consider the work of Hershey and Schoemaker (1980) on choices between a sure

loss and a gamble, as compared to deciding whether or not to buy insurance (which also involves a sure loss versus a gamble). Table 4 shows the different responses when structurally equivalent gambles are framed in terms of both an insurance and a gambling context. The results show a higher

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Insert Table 4 about here

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percentage of risk averse choices for the former. Why ? We argue that, relative to gambling, the insurance context induces a greater attitude toward caution (i.e., more weight is given to imagining values of the probability greater than the anchor), and this is reflected in different β parameters in the two contexts; specifically, $\beta_{insurance} > \beta_{gambling}$. This implies that $S(p_L)_{insurance} > S(p_L)_{gambling}$, such that greater risk aversion is observed in the insurance as compared to the gambling context.

Conclusion

The study of risk has been dominated by a single metaphor; the explicit lottery with stated probabilities and payoffs. However, as noted by Lopes (1983),

> The simple, static lottery or gamble is as indispensible to research on risk as is the fruitfly to genetics. The reason is obvious; lotteries, like fruitflies, provide a simplified laboratory model of the real world, one that displays its essential characteristics while allowing for the manipulation and control of important experimental variables. (p. 137)

We believe that it is time to move beyond the tidy experiments and axiomizations built upon the explicit lottery. The real world of risk involves ambiguous probabilities, dependencies between probabilities and utilities, context and framing effects (Thaler, 1985; Tversky & Kahneman, 1981), regret (Bell,1982), "illusions of control" (Langer, 1975), and superstitions (Skinner, 1966). Given the richness of the phenomena before us, our biggest risk would be to ignore them.

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Table 1

Ellsberg Paradox with Gains and Losses at Two Probability Levels

Conditions	Ambiguous urn	Nonambiguous urn	Indifference	Total
<u>Win $100</u>				
p = .5	25 (19%)	63 (47%)	45 (34%)	133
p = .001	48 (35%)	60 (43%)	30 (22%)	138
<u>Lose $100</u>				
p = .5	18 (14%)	40 (30%)	75 (56%)	133
p = .001	7 (5%)	106 (75%)	28 (20%)	141

Table 2

Median Buying and Selling Prices for Insurance

	Buyers		Sellers	
Probs.	(1) Nonambig.	(2) Ambig.	(3) Nonambig.	(4) Ambig.
.01	1,000	1,500	1,000	2,500
.35	35,000	35,000	37,500	52,500
.65	65,000	45,000	65,000	70,000
.90	82,500	60,000	90,000	90,000

Table 3

Median Buying and Selling Prices for Warranty

	Buyers		Sellers	
Probs.	(1) Nonambig.	(2) Ambig.	(3) Nonambig.	(4) Ambig.
.05	20	25	20	40
.25	90	50	100	120
.75	200	100	300	300

Table 4

**Effect of Insurance versus Gambling Context
For a Possible $10,000 Loss**

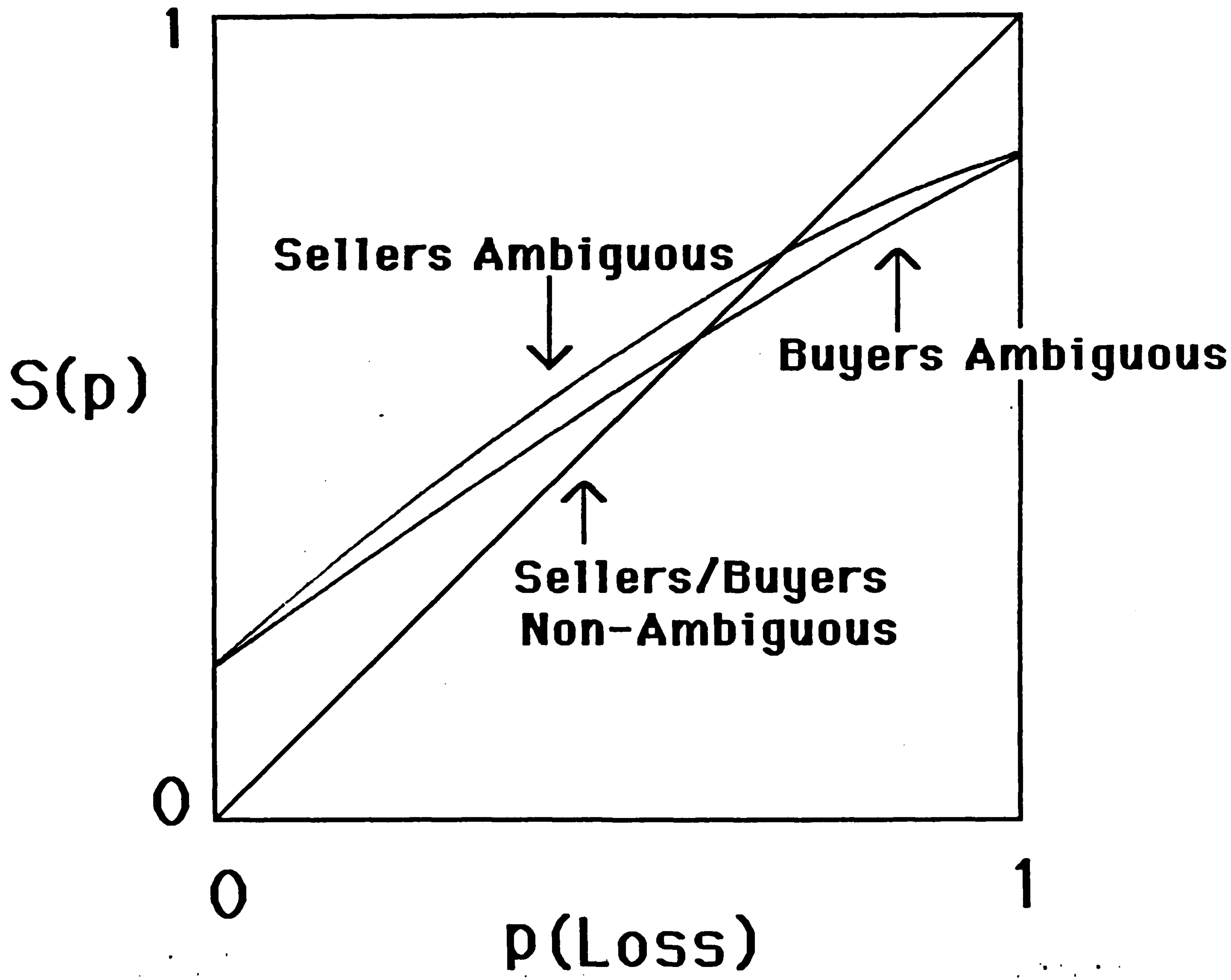
Probability	Sure Loss	% Preferring Sure Loss - Insurance	% Preferring Sure Loss - Gambling
.001	10	81	54
.01	100	66	46
.10	1000	59	29
.50	5000	39	32
.90	9000	34	24
.99	9900	27	22
.999	9990	17	17

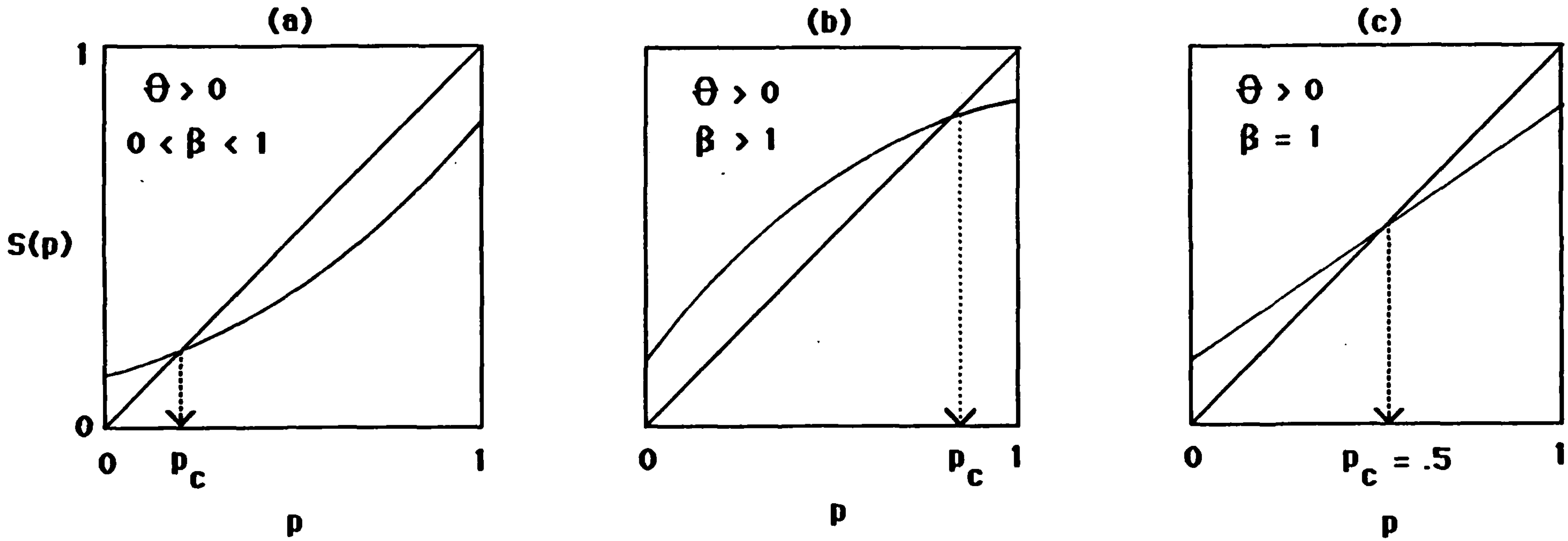
Figure Captions

Figure 1. S(p) as a function of p for values of θ and β.

Figure 2. Classification of insurance situations.

Figure 3. Approximate ambiguity functions for buyers and sellers of insurance.


1
S(p)
0
Sellers Ambiguous
Buyers Ambiguous
Sellers/Buyers
Non-Ambiguous
0
1
p(Loss)


(a)
(b)
(c)
S(p)
1
0
θ > 0
0 < β < 1
β > 1
β = 1
p_c
p_c = .5
p

		BUYERS	
		Nonambiguous	Ambiguous
SELLERS	Nonambig.	Well known processes (1)	Typical situation (2)
	Ambiguous	New technologies- inside information for buyers (3)	New technologies- processes poorly understood (4)

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